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An Artificial Neural Network Prediction Model of Respiratory Illness among Medical Students during Gross Anatomy Dissection Classes

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Abstract

Exposure to indoor air pollutants can cause adverse health outcomes. This study aimed to develop an Artificial Neural Network (ANN) model to predict respiratory illness among students during gross anatomy dissection classes. All participants were interviewed face-to-face using questionnaires. General information, gross anatomy laboratory room characteristics, and symptoms of respiratory illness during gross anatomy dissection were assessed. The environmental parameters related to indoor air quality, total fungi, and bacteria in a gross anatomy dissection room were measured. Pearson's correlation, spearman's rank correlation and regression analysis were used to analyse data. The findings revealed ten factors significantly associated with respiratory illness ($P < 0.05$). The six influencing variables including formaldehyde concentration (personal sampling), bacteria, relative humidity, fungi, time of gross anatomy dissection class, and formaldehyde concentration (area sampling) as tested using regression analysis. ANN model was then run to predict the respiratory illness from those six variables. Predictive accuracy was assessed by the Mean Absolute Deviation (MAD), Mean Absolute Percentage Error (MAPE), Mean Square Error (MSE), and Root Mean Square Error (RMSE) value. ANN model showed the least value of MAD, MAPE, MSE, and RMSE when comparing an error value of less than 10%. Therefore, the ANN model is accurate and valid for respiratory illness prediction in individuals in order to plan for solving problems according to the factors influencing the respiratory illness before starting a class. Further research is recommended to improve to model by large-sample-size research.

Keywords: Respiratory illness; Indoor air quality; Artificial neural network model; Gross anatomy dissection

1. Introduction

Indoor air quality (IAQ) is an essential issue for occupational and public health. People spend more than 90% of the day in indoor environments. Therefore, exposure to indoor air pollutants can increase the risk of developing adverse health outcomes. IAQ can be affected by toxic compounds, allergens, particulates, and infectious agents that can cause different respiratory illnesses (Cincinelli and Martellini, 2017; WHO, 2020). The symptoms of respiratory illnesses related to poor IAQ have been associated with the flu, including fever, chills, chest tightness, muscle aches, and cough. Also, asthma and asthma-like symptoms and severe lung and respiratory problems are likely to occur (Tran *et al.*, 2020).

In medical school environments with gross anatomy dissection, IAQ can directly influence the students who study in the class. The typical preparation of cadavers in gross anatomy laboratories is embalming fluid, which contains formaldehyde as a principal component. During the process of dissection, formaldehyde vapours are emitted from the cadavers, resulting in the exposure of medical students and their instructors to elevated levels of formaldehyde in the laboratory (Ohmichi *et al.,* 2006). Formaldehyde is described in the literature as a strong depressor of human health due to high toxic and carcinogenic potentials (WHO, 2006). Chronic exposure to formaldehyde causes cancer, and epidemiological studies show adverse effects on irritation of the eyes and respiratory tract's mucous membranes and skin irritation (Sahlberg *et al.,* 2013). In addition to formaldehyde, medical students are also exposed to indoor air pollutants such as carbon dioxide (CO_2), carbon monoxide (CO), total volatile organic compounds (TVOCs), temperature (°C), relative humidity (RH%), microbial air contamination in the indoor environment of a gross anatomy laboratory due to inappropriate indoor air ventilation systems, dissection of each part of the body, time of gross anatomy dissection class, and self-protection by wearing personal protective equipment (Page and Shear, 1998; Koren *et al.,* 1992; Mehta *et al.,* 2007; Maville and Huerta, 2013; Hatami *et al.,* 2014; Małecka-Adamowicz *et al.,* 2015; Mancebo and Wang, 2015; Goad and Gawkrodger, 2016; Azuma *et al.,* 2018; Brągosewska *et al.,* 2018).

Artificial neural network (ANN) is one of the intellectual tools for forecasting complex problems. ANN is computing systems constructed from a set of artificial neurons comparable to biological neural networks. The artificial neuron that receives a signal then processes it and can signal neurons connected to it. Each connection has a numeric weight that can be adjusted during the network's training, making the system adaptive to input patterns and revealing previously unknown relationships between given input and output variables (Manning *et al.,* 2014; Zhang, 2016). Unlike other modeling tools, ANN makes no prior assumptions concerning the data distribution. ANN can model highly non-linear relationships and can be trained to generalize when presented with a new data set. Moreover, it has a high possibility of finding the correct solution, even if a part of network layers is deleted or works incorrectly (Tu, 1996). As a powerful computational method, ANN has been widely used in the environmental, medical, and public health fields (Nyhan, 2014; Hu *et al.,* 2018; Maleki *et al.,* 2019).

With the severity of indoor air pollutants during the gross anatomy dissection classes, it is crucial to predict the associated adverse health outcome for providing proper actions and controlling strategies. This study aimed to develop the ANN model to predict respiratory illness among medical students during gross anatomy dissection classes.

2. Materials and methods

2.1 Study area and participants

A cross-sectional study was carried out among students who studied gross anatomy dissection. The sampling area was a gross anatomy dissection study room located on the 1st floor of the building in Thammasat University, Thailand. This gross anatomy dissection room is natural ventilation. Indoor air quality monitoring was conducted in four areas (Figure 1). Area A: contain 1 group of students (Group 1); Area B: contain 3 groups of students (Group 2, 5, and 8); Area C: contain 4 groups of students (Group 3, 4, 6, and 7); Area D: No students. All students in the same study section were randomly selected as participants. The students who had an intermittent study period in a gross anatomy dissection room, such as stopping to study for personal business, were excluded from participating in this study. As a result, 53 students were recruited as participants and provided signed and dated informed consent forms.

Figure 1. Indoor air quality monitoring area

2.2 Data collection and instruments

All participants were interviewed face-to-face using questionnaires. General information, gross anatomy laboratory room characteristics, and symptoms of respiratory illness during gross anatomy dissection were assessed. The questionnaires were developed and adopted from previous studies by researchers based on the severity level, which three experts approved before data collection with IOC; 0.70 - 1.00.

The environmental parameters related to indoor air quality, total fungi, and bacteria were measured using Indoor Air Quality (IAQ) meter and bio sampler impactor. The IAQ meter (Q-TRAK Indoor Air Quality Monitor Model 7575) was calibrated, measured of CO_2, CO, TVOCs, temperature, and RH%. The bio sampler impactor (Bio Sampler: SAS SUPER ISO 100) was calibrated and set up at flow 200-500 liters/minute with a dish containing trypticase soy agar and malt extract agar for identification of bacteria and fungi, respectively. Personal pump with sorbent tube [10% (2-hydroxymethyl) piperidine on XAD - 2, 120 mg/60 mg] was used for areas and personal sampling for formaldehyde concentration in the air sampling. Personal pumps were calibrated and set up for 0.01 to 0.10 liters/minute; NIOSH Method 2541 using the Gas Chromatography-Flame Ionization Detector (GC-FID) for analyzing the formaldehyde concentration in the air. For formaldehyde a limit of detection (LOD) based on calibration curve slope (R^2 = 0.997982) is 0.001 mg/m^3. After samples were completed, questionnaires were collected and analyzed.

2.3 Model development and data analysis

The data were analyzed using the SPSS version 18 (PASW serial no. 5082357). Descriptive statistics were used for analyzing the socio-demographic of the participants as well as gender, age, underlying diseases, and room characteristics. The analysis also included the number of hours the students spent studying daily and weekly. Pearson's correlation coefficient and spearman's rank correlation were used to determine the association between those variables, and respiratory illness.

There are several signs of respiratory illness to look out for. Each of these symptoms can be an indication that might be suffering from a respiratory illness. Six common signs including difficulty breathing, stubborn cough, breathing noisily, lingering chest pain, chronic mucus, and coughing up blood were used. These signs are converted as the prevalence of respiratory illness.

Furthermore, regression analysis was used to identify the factors influencing the respiratory illness. There were six influenced variables were examined using ANN. Mean Absolute Deviation (MAD), Mean Absolute Error (MAE), Mean Square Error (MSE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE), these values were specified the least error prediction models. If the error values are less than 10%, 10% to 20%, 20% to 50%, and more than 50%, then the model is high, good, reasonable, and inaccurate prediction, respectively (Frechtling, 2001).

2.4 Ethical approval

This research project was reviewed and approved by the Human Research Ethics Committee of Thammasat University, No.3. (Ethical approval number 061/2561; Approval date: September 5, 2018)

Table 1. General characteristics and respiratory illness of the medical students (n=53)

Characteristics		Part of gross anatomy dissection, n (%)					
		Week 1	Week 2	Week 3	Week 4	Week 5	Week 6
Gender	Male	16 (30.2)	16 (30.2)	16 (30.2)	16 (30.2)	16 (30.2)	16 (30.2)
	Female	37 (69.8)	37 (69.8)	37 (69.8)	37 (69.8)	37 (69.8)	37 (69.8)
Age (Years old) $\bar{X}$= 20.45; SD=2.074	19	24 (45.3)	24 (45.3)	24 (45.3)	24 (45.3)	24 (45.3)	24 (45.3)
	20	16 (30.2)	16 (30.2)	16 (30.2)	16 (30.2)	16 (30.2)	16 (30.2)
	21	3 (5.7)	3 (5.7)	3 (5.7)	3 (5.7)	3 (5.7)	3 (5.7)
	23	2 (3.8)	2 (3.8)	2 (3.8)	2 (3.8)	2 (3.8)	2 (3.8)
	24	2 (3.8)	2 (3.8)	2 (3.8)	2 (3.8)	2 (3.8)	2 (3.8)
	25	5 (9.4)	5 (9.4)	5 (9.4)	5 (9.4)	5 (9.4)	5 (9.4)
	26	1 (1.9)	1 (1.9)	1 (1.9)	1 (1.9)	1 (1.9)	1 (1.9)
Glasses wearing without contact lens	No	48 (90.6)	47 (88.7)	45 (84.9)	47 (88.7)	48 (90.6)	48 (90.6)
	Yes	5 (9.4)	6 (11.3)	8 (15.1)	6 (11.3)	5 (9.4)	5 (9.4)
Underlying diseases	No	43 (81.1)	43 (81.1)	43 (81.1)	43 (81.1)	43 (81.1)	43 (81.1)
	Yes	10 (18.9)	10 (18.9)	10 (18.9)	10 (18.9)	10 (18.9)	10 (18.9)
Time of gross anatomy dissection class (Hours) $\bar{X}$= 3.12; SD=0.334	3	50 (94.3)	37 (69.8)	45 (84.9)	52 (98.1)	51 (96.2)	44 (83.0)
	4	3 (5.7)	15 (28.3)	8 (15.1)	1 (1.9)	2 (3.8)	9 (17.0)
	5	0 (0)	1 (1.9)	0 (0)	0 (0)	0 (0)	0 (0)
Respiratory illness	No	34 (64.2)	36 (67.9)	42 (79.2)	45 (84.9)	44 (83.0)	34 (64.2)
	Yes	19 (35.8)	17 (32.1)	11 (20.8)	8 (15.1)	9 (17.0)	19 (35.8)

Week 1 = Back, Week 2 = Upper limp, Week 3 = Superficial face, Week 4 = Deep face, Week 5 = Anterior neck, Week 6 = Abdominal

3. Results and Discussion

3.1 General information, gross anatomy laboratory room characteristics survey and respiratory illness

The general profile and respiratory illness of the participants were illustrated in Table 1. There were 53 medical students, including 37 females and 16 males. The results revealed that 69.8% of the female medical students were between 19-26 years old, and 88.7% of subjects wore glasses without contact lens. About 81.1% of the medical students had no underlying diseases, and more than 88.0% took 3 hours for gross anatomy dissection class per time. Moreover, 26.1% of them reported that they had respiratory illness which confirmed previous studies (Sahlberg *et al.,* 2013; Merrill, 2008; Sun *et al.,* 2013; Lu *et al.,* 2016; Takaoka *et al.,* 2016; Reuben *et al.,* 2019). From a gross anatomy laboratory room survey, the gross anatomy laboratory room is ventilated naturally. Thirty-four windows allowed outside air to enter the room, 23 ceiling fans active while gross anatomy dissection, and 100 ceiling lights activated during gross anatomy dissection.

3.2 Indoor air Quality

The indoor air concentrations in a dose-dependent manner for biological parameters range from 122.5 - 535.0 CFU/m^3 and 137.5 - 775.0 CFU/m^3 for total fungi and total bacteria in anatomy room, respectively. Regarding the results, most of the high number of colonies counts per 1 m^3 of air was in anatomy of back and suboccipital region dissection. The results showed that two areas of fungal and three areas of bacteria were found higher than WHO Standard 2010 and ACGIH Standard 1989 (WHO, 2010; ACGIH, 1999). Similarly, a 2010 research in the USA found that the mean concentration in indoor airborne cultivable bacteria and fungi was similar (An *et al.,* 2004) while some study found higher than 10 times (Madureira *et al.,* 2015).

For TVOCs concentration, the mean concentration was 1.60 ppm (range 1-2 ppm). All of the sampling points were below the recommended limits (Department of Health (Thailand), 2020). Based on formaldehyde concentration measurement in both area and personal sampling, the mean concentration in laboratory area was 0.5312 ppm (range 0.0421 – 1.0801 ppm). More than 75% of the sampling were below the permissible exposure limits of Occupational Safety and Health Administration: OSHA ($\leq$ 0.75 ppm) except point number 3 and 4. The highest concentration was in anatomy of back and sub occipital region dissection sections. This affirms a similar study in formaldehyde exposure among medical students during anatomy laboratory which reported that sections of anatomy regions related to formaldehyde have higher concentrations (Kamonwan *et al.,* 2014). On the other hand, half of them from measuring the formaldehyde concentration on personal sampling showed that exceeded OSHA and the mean concentration was 0.6655 ppm (range 0.0437 – 1.3841 ppm). The highest concentration was in group 7 (area B) in anatomy of back and suboccipital region dissection.

The results demonstrated that all of the temperature and relative humidity were higher than American Society of Heating, Refrigerating, and Air-conditioning Engineers (ASHRAE Standard 55-2010) with range of 22.0 - 26.1^{o}C and 30.0 - 65.0%, respectively. This may be according to the natural ventilation in the laboratory. The mean temperature of sampling areas was 31.06^{o}C, in muscle of facial expression and mastication dissection and found high temperature in area A and C. Relative humidity measured range from 64.0 - 82.6 % (mean 72.8 %). The highest located was area D with anatomy of back and suboccipital region dissection. This study found that CO_2 and CO concentration were below the recommended limits of ASHRAE 62 (less than 700 ppm and less than 9 ppm, respectively). The mean CO_2 concentration was 459.5 ppm with range from 423.0 – 511.0 ppm while CO concentration range from 0.60 - 3.80 ppm (mean 1.72 ppm).

3.3 Regression analysis

The association between independent variables and respiratory illness were analysed using spearman's rank correlation coefficients and pearson's correlation coefficient as shown in Table 2. Regression analysis engulfs ten influenced variables from those analysis. There were six influenced variables were examined using regression analysis as shown in Table 3. The results further showed that between temperature and respiratory illness, there was a high negative correlation which according to Maria D'Amato *et al.* (2018) has been found on indoor temperature below 24°C and relative humidity between 40% and 60%, there is a risk of negative consequences on the respiratory tract. While between CO and respiratory illness, there was a low negative correlation which according to Linwei Tian *et al.* (2013) has been found that short-term exposure to CO was associated with decreased risk of hospital admissions for Respiratory Tract Infections: RTI. On the other hand, the relationship between relative humidity, fungi in indoor air, formaldehyde concentration both personal sampling and area sampling and respiratory illness was found to have a high positive correlation while the association between bacteria in indoor air, CO_2 and respiratory illness had low positive correlation. This is found to be similar to other studies on indoor air quality and respiratory illness (Sahlberg *et al.,* 2013; Sun *et al.,* 2013; Lu *et al.,* 2016; Kamonwan *et al.,* 2014).

A comparison of the difference between the calculated result and the actual result was then evaluated. There were four error values: MAE, MSE, RMSE, and MAPE which were developed from ANN model by considering Equation (1)-(4).

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|A_t - F_t| \quad (1)$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(A_t - F_t)^2 \quad (2)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(A_t - F_t)^2} \quad (3)$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \times 100 \quad (4)$$

Where
A_t = Actual of respiratory illness prevalence rate
F_t = Predicting the respiratory illness prevalence rate
i = Number of medical students
n = Total number of medical students

3.4 Artificial neural network (ANN) model

ANN is a computer model that simulates the function of the human brain. Waikato Environment for Knowledge Analysis (WEKA) was used for creating the multilayer perceptron (MLP) with the back-propagation learning algorithm. It has been widely used in previous research and can also be used for making future predictions based on the data used to create models (Gedeon *et al.,* 1995).

Table 2. Association between independent variables and respiratory illness

Independent variables	Spearman's correlation coefficient	Pearson's correlation coefficient	*p-value*
Part of gross anatomy dissection	-	-0.996	<0.001*
Time of gross anatomy dissection class	0.130	-	0.034*
Fungi in indoor air	0.649	-	<0.001*
Bacteria in indoor air	0.321	-	<0.001*
Formaldehyde concentration (Personal sampling)	0.595	-	<0.001*
Formaldehyde concentration (Area sampling)	0.574	-	<0.001*
Temperature	-0.544	-	<0.001*
Relative Humidity	0.742	-	<0.001*
CO_2	0.202	-	<0.001*
CO	-0.235	-	<0.001*

* *p*-value <0.05

ANN model was to consider an error at the output layer that propagates backward to the input layer through the hidden layer in the network until receiving the final desired output. Gradient Descent (GD) is an optimization method to find a minimum of a function. In back-propagation, it is used to iteratively update the weights of interconnections in order to minimize the output error (Lee, 2008). Before solving a problem, ANN must be trained continues until 100,000 epochs. The database was divided into two sets: training and testing set, in a 70/30 ratio (Bishop, 1995). MLP consisted of 6 input variables, 1 output variable, 10 hidden nodes, changing 1 - 10 nodes, learning rate was between 0.05 and 0.5, and momentum was between 0.05 and 0.5 as shown in Figure 2. A comparison of the difference between the calculated result and the actual result was then evaluated. Four error values: MAE, MSE, RMSE, and MAPE together with the value of predictive model were expressed following the Equation (1) - (6). These values were specified the least error prediction models. If the error values are less than 10%, 10% to 20%, 20% to 50%, and more than 50%, then the model is high, good, reasonable, and inaccurate prediction, respectively (Frechtling, 2001). MAPE was given the least predicting errors, which according with the global performance of trained ANN by comparing with MAPE (Delen *et al.,* 2006). The results of predictive model were shown in Table 4. Calculation of each hidden node value with a sigmoid activate function was shown in Figure 3. ANN model was run to forecast the respiratory illness prevalence rate from six influential variables quite successfully which according to Hu *et al.* (2018) has been found that ANN model can be used for prediction of influenza-like illness based on the improved artificial tree algorithm and artificial neural network as highly accurate forecasting. It also corresponds with Nyman *et al.*

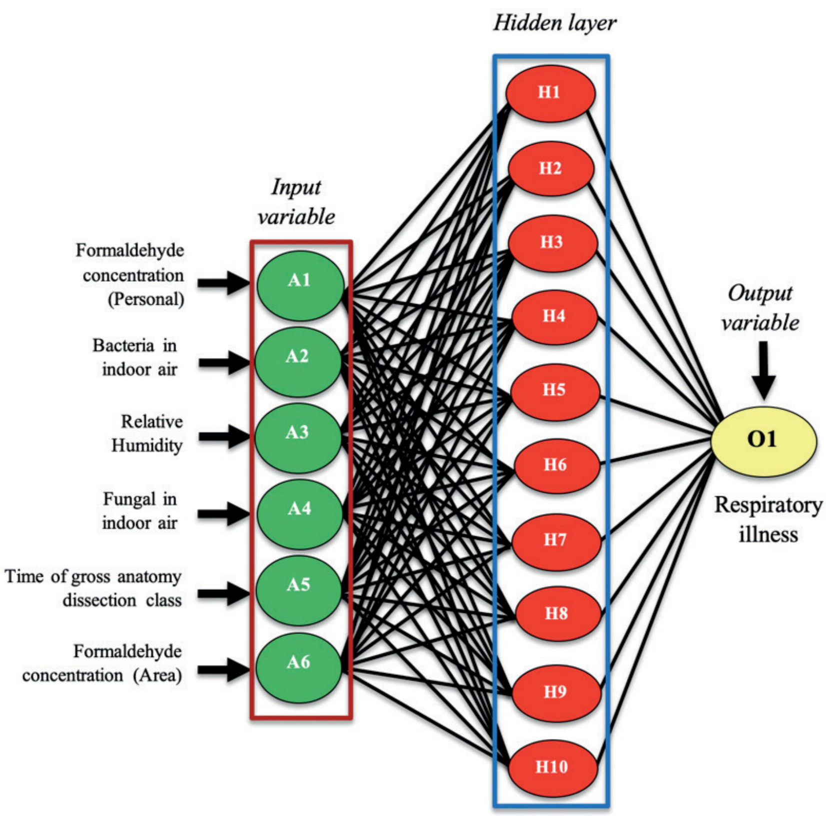

Figure 2. Multilayer perceptron (MLP) of ANN model

(2014) has been found that ANN model can be used for predicting minute ventilation and lung deposited dose in commuting cyclists and showed the least error when compared to other models. ANN can be retrained whenever new information becomes available. However, a neural network, as a prediction tool, can only be as good as the quality of the training data for the task at hand. If the available data are not representative, the network cannot be expected to perform well.

$$X = A_1W_{11} + A_2W_{21} + A_3W_{31} + \ldots + A_nW_{n1} + W_o \quad (5)$$

$$f(x) = \frac{1}{1+e^{-x}} \quad (6)$$

Where

X = Sum of each hidden node

A_n = Attribute or input variable ($A1, A2, \ldots, An$)

W_{n1} = Attribute's weight of each hidden node ($W_{11}, W_{21}, \ldots, W_{n1}$)

W_o = Threshold

Table 4. Error comparison and predictive ANN model.

No.	Independent variables	Predictive ANN model (6-10-1)	Actual value	MAE	MAPE	MSE	RMSE
1	(1) Formaldehyde concentration (Personal) (2) Bacteria in indoor air (3) Relative Humidity (4) Fungi in indoor air (5) Time of gross anatomy dissection class (6) Formaldehyde concentration (Area)	0.30	0.29	0.03	11.11	0.00	0.02
2		0.30	0.28	0.07	22.22	0.00	0.04
3		0.30	0.31	0.03	11.11	0.00	0.02
4		0.30	0.29	0.03	11.11	0.00	0.02
5		0.30	0.29	0.03	11.11	0.00	0.02
.		.	.	.	.	.	.
.		.	.	.	.	.	.
.		.	.	.	.	.	.
52		0.30	0.30	0.00	0.00	0.00	0.00
53		0.30	0.30	0.00	0.00	0.00	0.00
Total				0.03	9.64	0.00	0.02

MAE, mean absolute error; MAPE, mean absolute percentage error; MSE, mean square error, RMSE, root mean square error

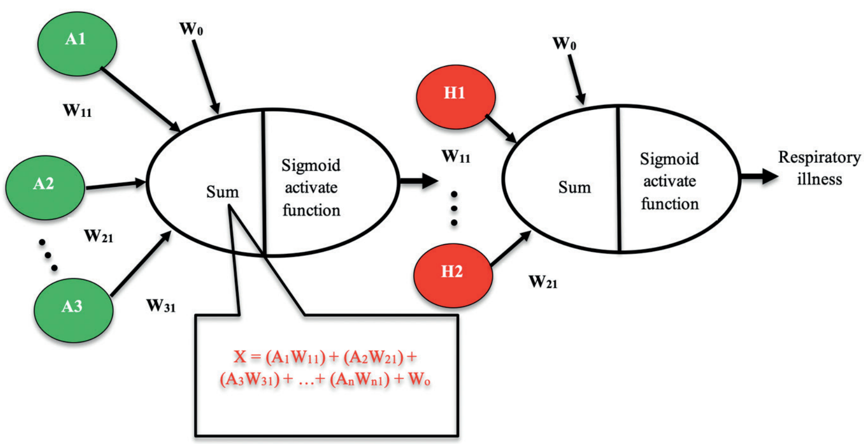

Figure 3. Attribute summation of each hidden node

4. Conclusions

This cross-sectional study was limited to a particular geographic area because data are collected from a small population and small study sites. However, this study was focused on medical students, which can be the baseline for related agencies. Thus, university policy implementation and risk communication will be introduced to the students and staff to promote safety programs and sustain behaviour enhancement. The engineering approach should be performed in the laboratory room to control indoor air quality in the gross anatomy for further direction.

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Conflict of Interest Disclosure

No conflict of interest disclosure.

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